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Ito's Rule: $df(X_t) = \frac{df}{dx} \cdot dX_t + \frac{1}{2} \frac{d^2f}{dx^2} (dX_t)^2$

Problem 1

a) $f(x) = e^{x^2-1}$

$$\frac{df}{dx} = 2x \cdot e^{x^2-1}$$

$$dX_t = dW_t$$

$$X_t = W_t$$

$$(4.25): (dW_t)^2 = dt$$

$$f'(X_t) = 2X_t \cdot e^{X_t^2-1}$$

$$\begin{aligned} f''(X_t) &= 2e^{X_t^2-1} + 2X_t \cdot (2X_t) e^{X_t^2-1} \\ &= (2 + 4X_t^2) e^{X_t^2-1} \end{aligned}$$

$$dZ_t = df(X_t) = f'(X_t) dX_t + \frac{1}{2} f''(X_t) (dX_t)^2$$

$$= 2W_t e^{W_t^2-1} \cdot dW_t + \frac{1}{2} \cdot (2 + 4W_t^2) e^{W_t^2-1} \cdot (dW_t)^2$$

$$dZ_t = (1 + 2W_t^2) e^{W_t^2-1} \cdot dt + 2W_t e^{W_t^2-1} dW_t //$$

1

Problem 1

b) $f(x_t) = e^{x_t} = f'(x_t) = f''(x_t)$

$$dz_t = f'(x_t) dx_t + \frac{1}{2} f''(x_t) (dx_t)^2$$

$$= e^{W_t^2-1} \cdot (dt + 2W_t dW_t) + \frac{1}{2} e^{W_t^2-1} (dt + 2W_t dW_t)^2$$

$$(dt + 2W_t dW_t)^2 = (dt)^2 + 4W_t dW_t dt + 4W_t^2 dt = 0 + 0 + 4W_t^2 dt$$

$$\text{L4.21: } (dt)^2 = 0$$

$$(dW_t)(dt) = 0$$

$$dz_t = e^{W_t^2-1} dt + 2W_t e^{W_t^2-1} dW_t + \frac{1}{2} e^{W_t^2-1} (4W_t^2 dt)$$

$$dz_t = (1 + 2W_t^2) e^{W_t^2-1} dt + 2W_t e^{W_t^2-1} dW_t //$$

c) L4.12: X_t is a martingale iff $M_t = 0$ for all $t > 0$

$$dX_t = M_t dt + \sigma_t dW_t$$

drift term, M_t must be 0.

here, drift term is $(1 + 2W_t^2) e^{W_t^2-1}$ which is not 0

for all $t > 0$, with probability 1.

$\rightarrow Z$ is not a martingale //

Problem 2

$$\begin{aligned} a) \quad d(e^{k_t})d(X_t) &= \{k e^{k_t} dt\} \{k(\theta - X_t)dt + \sigma dW_t\} \\ &= \underbrace{k^2 e^{k_t} (\theta - X_t) (dt)^2}_0 + \underbrace{k \sigma e^{k_t} \cdot \sigma \cdot dW_t \cdot dt}_0 \quad (4.21) \end{aligned}$$

$$d(e^{k_t})d(X_t) = 0$$

$$(4.33) \quad d(X_t Y_t) = Y_t d(X_t) + X_t d(Y_t) + d(X_t) d(Y_t)$$

$$\begin{aligned} d(e^{k_t} X_t) &= e^{k_t} d(X_t) + X_t d(e^{k_t}) + \underbrace{d(e^{k_t}) \cdot d(X_t)}_0 \\ &= e^{k_t} (k(\theta - X_t)dt + \sigma dW_t) + X_t \cdot k e^{k_t} dt \\ &= e^{k_t} (k\theta dt - k X_t dt + \sigma dW_t) + X_t \cdot k e^{k_t} dt \\ &= e^{k_t} k \cdot \theta dt - \cancel{e^{k_t} k X_t dt} + e^{k_t} \sigma dW_t + \cancel{X_t \cdot k e^{k_t} dt} \end{aligned}$$

$$d(e^{k_t} X_t) = k \cdot \theta \cdot e^{k_t} dt + \sigma e^{k_t} dW_t$$

$$\text{if } Z_t = e^{k_t} \cdot X_t,$$

$$Z_t = Z_0 + \int_0^T k \cdot \theta e^{k_t} dt + \int_0^T \sigma \cdot e^{k_t} dW_t$$

$$e^{k_T} X_T = e^{k_0} X_0 + \int_0^T k \theta e^{k_t} dt + \int_0^T \sigma \cdot e^{k_t} dW_t$$

$$e^{k_T} X_T = X_0 + \int_0^T k \cdot \theta e^{k_t} dt + \int_0^T \sigma \cdot e^{k_t} dW_t //$$

↓
Constant

↓
Riemann integral
w.r.t. dt

↓
Itô integral
w.r.t. d

Problem 2

$$\begin{aligned} b) \int_0^T k\theta e^{kt} dt &= k\theta \int_0^T e^u \cdot \frac{1}{k} du = \theta \int_0^T e^u du = \theta e^u \Big|_{t=0}^{t=T} = \theta e^{kt} \Big|_{t=0}^{t=T} \\ \left. \begin{array}{l} u = kt \\ du = k \\ \frac{du}{dt} = k \end{array} \right| &= \theta (e^{kT} - e^{k \cdot 0}) = \theta (e^{kT} - 1) \end{aligned}$$

$$e^{kT} X_T = X_0 + \theta (e^{kT} - 1) + \int_0^T \sigma \cdot e^{kt} dW_t$$

$$X_T = \frac{X_0}{e^{kT}} + \theta \left(1 - \frac{1}{e^{kT}}\right) + \int_0^T \sigma \cdot e^{kt-kT} dW_t \rightarrow 0$$

$$E(X_t) = X_0 E(e^{kt}) + \theta E(1 - e^{-kt}) + E\left(\int_0^T \sigma e^{k(t-T)} dW_t\right)$$

(4.11), expected value of any Itô integral is 0 \nearrow this is Itô integral

$$E(X_t) = X_0 e^{kT} + \theta (1 - e^{-kT}) //$$

Problem 2

b) Variance of X_t

$$X_t = \underbrace{\frac{X_0}{e^{kT}} + \theta(1 - e^{-kT})}_{\text{Constant}} + \int_0^T \sigma \cdot e^{k(t-T)} dW_t$$

Since the first 2 terms are constant, $\text{Var}(X_t)$ depends on $\int_0^T \sigma \cdot e^{k(t-T)} dW_t = \int_0^T \beta_t dW_t$, where $\beta_t = \sigma \cdot e^{k(t-T)}$

$$\int_0^T \beta_t dW_t \sim \text{Normal} \left(0, \int_0^T \beta_t^2 dt \right)$$

$$\text{Var}(X_t) = \text{Var} \left(\int_0^T \beta_t dW_t \right) = \int_0^T \beta_t^2 dt = \int_0^T \sigma^2 \cdot e^{2k(t-T)} dt$$

$$\begin{cases} u = t-T \\ du = dt \end{cases}$$

$$\text{Var}(X_t) = \sigma^2 \cdot \int e^{2k \cdot u} du = (\sigma^2) \cdot \frac{1}{2k} \cdot e^{2k \cdot u} \Big|_{t=0}^{t=T}$$

$$= \frac{\sigma^2}{2k} \cdot e^{2k(t-T)} \Big|_{t=0}^{t=T} = \frac{\sigma^2}{2k} \cdot (e^{2k(T-T)} - e^{2k(0-T)})$$

$$\text{Var}(X_t) = \frac{\sigma^2}{2k} (1 - e^{-2kT})$$

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Problem 3

a) long-term-mean is around 10 $\rightarrow \theta = 10$
small variability $\rightarrow k = 8 //$

b) long-term mean is around 15 $\rightarrow \theta = 15$
big variability $\rightarrow k = 3 //$

c) long-term mean is around 15 $\rightarrow \theta = 15$
small variability $\rightarrow k = 8 //$

d) long-term mean is around 10 $\rightarrow \theta = 10$
big variability $\rightarrow k = 3 //$

e) long-term mean is around 5 $\rightarrow \theta = 5$
big variability $\rightarrow k = 3 //$

f) long-term mean is around 5 $\rightarrow \theta = 5$
small variability $\rightarrow k = 8 //$

$k = 8 \rightarrow$ higher mean reversion rate \rightarrow smaller variability

$k = 3 \rightarrow$ smaller mean reversion rate \rightarrow bigger variability.

b